Statistical procedures for defining and detecting the CVPIA natural Chinook salmon production doubling goal

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February 25, 2004

EXECUTIVE SUMMARY

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   A mandate of Title 34 – Central Valley Project Improvement Act (of Public Law 102-575), CVPIA, is to "develop ... and implement a program which makes all reasonable efforts to ensure that, by the year 2002, natural production of anadromous fish in Central Valley rivers and streams will be sustainable, on a long term basis at levels not less than twice the average levels attained during the period of 1967-1991". In this report we develop statistical procedures aimed at comparing natural production levels in the 1967-1991 period and in years since then and we present ideas for methods to determine the sustainability of natural production levels observed during a given period.

1. **Assessing doubling versus assessing sustainability.** The problem of determining whether a doubling of natural production has occurred is primarily a problem of statistically estimating natural production for a given stream and a particular time period. The problem of assessing sustainability is more difficult in that it includes both estimating natural production and also determining the reasons for particular observed levels of production. Solutions to this latter problem involve modeling changes in underlying life history parameters, especially expected juvenile survival rates, while statistically controlling for both demographic and environmental variation.

2. **Complications to assessing doubling.** Statistical procedures which aim to compare the natural production levels of anadromous fish in Central Valley rivers and streams in the period 1967-1991 with later periods are complicated by two factors which make standard approaches, e.g. two sample t-tests, inadequate. One factor is measurement error in natural production estimates. Measurement error includes variance and bias. The second factor is temporal dependence in natural production levels between adjacent years, where the dependency is due to the fact that progeny of the same cohort contribute to the natural production in multiple years.

3. **Recommended statistical alternative to assessing doubling.** We argue that state-space models are an appropriate statistical framework for accounting for both measurement error and temporal dependence simultaneously. State-space models are models for two time series running in parallel, where one time series reflects the true state of nature, in the present case the actual natural production levels distinguished by age-class, sex, etc., and the second time series consists of error-contaminated and temporally correlated estimates of the first series.

4. **Concerns regarding available data.** While we believe that state-space models are the proper statistical tool for comparing natural production levels in different periods, we have grave concerns over the quality of estimates of natural production in both the 1967-1991 period and in years since then. In particular the rationale behind estimates of the proportion of total production attributable to hatchery fish is extremely difficult to determine and

estimates of the imprecision and bias of the estimates are lacking. For state-space models to be successfully implemented, measures of the bias and imprecision of natural production estimates are needed. For the point estimates of natural production during the historical period of 1967-1991, statistical measures of accuracy and precision need to be calculated. With future analyses in mind, we emphasize the need for immediate implementation of statistically sound tagging, marking, and sampling schemes with associated procedures for separately estimating hatchery and natural production on a stream by stream basis. This involves at a minimum the tagging of several well-chosen hatchery releases meant to serve as surrogates for the various Central Valley natural stocks that cannot themselves be tagged in adequate numbers.

5. **Recommended statistical alternative to assessing sustainability.** Determining whether a given level of natural production observed during a particular period is sustainable involves more than a state-space model framework. The essential issue is whether changes in habitat have led to, or *caused*, fundamental changes in the environment relevant to the natural production of anadromous fishes. We formulate a measure of average natural production that is independent of environmental variation, which is based on recruitment parameters. Determining whether changes in this average natural production measure are due to ecosystem restoration efforts requires, preferably, the inclusion in the state-space model of natural production for control sites with measurements made in the 1967-1991 period and in a later period or, at least, the inclusion of covariates in the state-space model structure that aim to control for random environmental effects.

6. **Future work.** To successfully apply state-space models to the twin problems of assessing doubling and assessing sustainability, work is required on three fronts.

   (a) **Past data analysis.** The magnitude of errors of existing estimates of natural production during the baseline period and since 1992 may be very large. Any analysis methods seeking to compare natural production estimates between the baseline and later periods, including state-space models, must somehow account for such possibly large errors. We suspect that careful data analyses might allow one to develop some decent notions of the kinds of errors that may exist in tabulated estimates of natural production, but we believe substantial effort will be required to generate such notions.

   (b) **Future data generation.** A coordinated marking, tagging, sampling, and tag recovery program based on hatchery Chinook salmon reared in the Sacramento-San Joaquin needs to be implemented with the aim of using hatchery fish as surrogates for naturally produced fish. Marking and tagging of naturally produced juvenile fish, to the degree possible, is also needed to determine how well surrogate hatchery fish actually represent naturally produced fish. Sampling of ocean catches must of course continue, but in addition sampling of freshwater catches (e.g., creel surveys) needs to be reinstated. System-wide coordinated sampling of and estimation of escapement is needed for all the watersheds in the system, and standard errors for the escapement estimates need to be reported. Aging and sexing of at least subsamples of escapement data should be done, too, and the resulting information would be used for separating hatchery fish from wild

fish and estimation of natural production, for determining sustainability, and to account for between year dependence of production estimates.

(c) **State-space model formulation, development, and application.** A substantial research effort would be required to develop state-space models that could be used to assess doubling and also assess sustainability. Many of the basic ideas of the formulation have been developed in the report but alternative formulations for various components of the life history process need to be considered. Additionally the inclusion in the state-space model of either control sites, as in a BACI (Before-After Control-Impact) design, or covariates that reflect freshwater and marine survival conditions, requires considerable thought. Finally, computer programs need to be written to implement the state-space model and allow application of the model to real data sets.

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1 Introduction

One of the mandates of Title 34 – Central Valley Project Improvement Act (of Public Law 102-575), CVPIA, is to "develop ... and implement a program which makes all reasonable efforts to ensure that, by the year 2002, natural production of anadromous fish in Central Valley rivers and streams will be sustainable, on a long term basis at levels not less than twice the average levels attained during the period of 1967-1991". The wording of this mandate was such that alternative interpretations were possible; e.g., alternative definitions of natural and sustainable are possible.

The US Fish and Wildlife Service (USFWS) formed a workgroup to more clearly define and interpret the meaning of the mandate. The workgroup produced a document, "Final Restoration Plan for the Anadromous Fish Restoration Program" (USFWS, 2001), which includes an appendix titled "AFRP Position Paper". The position paper provides definitions for key terms in the mandate as well as an interpretation of the intent of Title 34. Here we summarize just two definitions that are pertinent to our report: natural production and sustainability.

Natural production is defined on an annual basis for a given naturally produced stock and it is the total catch and escapement within a specified year-long period. Assuming that fisheries take place beginning as early as April in a given year and proceed through the spawning season, which may continue as late as February of the following year, the total natural production for a given population is equal to the sum of the ocean and freshwater catches and freshwater spawning escapement that are attributed to natural spawning of that population in previous years. By this definition, returning adults that were survivors of fish released from hatcheries are not included in natural production, but returning adults that are survivors of fish produced via natural spawning, irrespective of the origin of adult parents, are included in natural production. Let P_{srt} denote the natural production for fish that were born in stream s of race r during "year" t. Then P_{srt} is calculated by

$$P_{srt} \;=\; \sum_a C_{OC,srta} + \sum_a C_{FW,srta} + \sum_a Esc_{N,srta} + \sum_a Esc_{H,srta},$$

where C_{OC} and C_{FW} are ocean and freshwater catches, Esc_N is escapement that spawned naturally, and Esc_H is escapement (of naturally produced fish) that strayed to hatcheries, with summation over all relevant age classes (denoted by a). Each of the above components can be further partitioned spatially, and, in the case of catch, by gear type (or commercial versus sport designation). For brevity when production is referred to in the remainder of this report it will designate the natural production for a particular stream, and is distinct from a stream's hatchery production (if it has a hatchery) and from a stream's total production, which is the sum of natural and hatchery production.

The problem of separating the contribution of hatchery fish to catch or escapement from the contribution from natural fish is a distinct statistical estimation problem that we do not address in

this report. Newman, Hicks, and Hankin (2004) do however present different statistical procedures for making such distinct estimates, all of which rely upon the use of tagged hatchery releases meant to serve as surrogates for designated naturally produced populations.

Regarding the second key term, sustainability, the USFWS (2001) position paper states that production levels are "sustainable when they are maintained under the entire range of conditions resulting from legal human activities, as superimposed on natural variability inherent in the system". Thus, a production level calculated during a period of much better than average ocean conditions is not a sustainable level if all other things remain unchanged relative to the baseline period of 1967-1991. For example, suppose average marine survival for smolts to age 2 (prior to maturation) was 1% during the baseline period and then became 2% during a later period. Suppose also that freshwater conditions (egg to smolt survival, available spawning habitat) remained the same for the two periods. Then average production will have doubled, but it would not be considered sustainable because marine conditions are part of the natural variability inherent in the system, beyond the deliberate manipulation of man. We note also that production can be greatly affected by changes in the age-specific harvest rates and an example of the impact on production due to differences in harvest rates alone is given in Appendix A.

Related to this definition of sustainable is the USFWS (2001) position that habitat restoration is the primary intended means of increasing anadromous fish production. It is further noted that habitat restoration includes increasing the productivity of existing habitat as well as increasing the amount of habitat.

The purpose of this report is to present statistical procedures that could be used to determine whether the mandate of Title 34 has been, or is being met. One set of procedures is focused on detecting, or determining whether, a doubling of natural production has occurred. These procedures can be roughly categorized as being either estimation or testing procedures. The other set of procedures aims to determine whether or not sustainable increases in production have occurred. These latter procedures can be approximately viewed as descriptive or explanatory modeling procedures. The nomenclature is not exact in that the estimation or testing procedures are based on underlying statistical models, but such models may provide neither explanation nor insight into why production might have changed nor may they indicate whether or not resulting production levels are sustainable.

The structure of the remainder of the report is as follows. The next three sections (Sections 2, 3, 4) focus on answering the question: "Has doubling occurred?". In Section 2 we present two idealized situations for a change in current production levels relative to baseline production along with some simple statistical procedures. In Section 3 departures from the idealized situation are discussed, in particular problems with data quality and the complications of environmental and demographic stochasticity are described. In Section 4 a statistical framework called a state-space model is presented and formulated as a tool for modeling production in the presence of error in the estimates of production and temporal dependence between annual production levels. Section 5 focuses on the question: "Assuming doubling has occurred, is it sustainable?". The report ends with discussion (Section 6).

We note here that salmon are the anadromous species that we use for demonstration and are

the species that we have focused on in earlier work aimed at developing production estimation procedures (Newman, Hicks, and Hankin, 2004). The other anadromous species identified by Title 34 (striped bass, sturgeon, and shad) are not addressed specifically but some of the statistical procedures proposed herein could be applied, perhaps with minor modification, assuming the necessary data are gathered for those species.

2   Idealized scenarios and statistical procedures

We present two idealized scenarios for a doubling of production to occur following the baseline period of 1967-1991. For both scenarios we assume perfect information, namely no measurement or estimation error in the production values. Process variation, demographic and environmental stochasticity, exists but is assumed constant. The two scenarios are plotted in Figure 1. In the first case (Figure 1 a), labeled sudden increase, there is an immediate and exact doubling of the mean production beginning in 1992. In the second case (Figure 1 b), labeled linear increase, there is a steady upward linear trend in the mean production level such that average production in 2001 (ten years after the baseline period) exactly equals twice the baseline period average and then the average production remains constant from then on. If in fact production should more than double, the ability to determine whether production has *at least* doubled will increase; this point is emphasized in the later section on a Bayesian solution.

The examples were based on the estimated baseline values for Deer Creek fall-run Chinook salmon production. In the sudden increase case, the production values are normally distributed with means, μ_B (B for before) and μ_A (A for after), and a constant standard deviation (in the figure, σ=400); namely,

$$P_t \sim \left\{ \begin{array}{ll} \text{Normal}(\mu_B, \sigma) & \text{t}= 1967, \ldots, 1991 \\ \text{Normal}(\mu_A = 2 * \mu_B, \sigma) & \text{t}= 1992, \ldots \end{array} \right\}$$

In the linear trend case,

$$P_t \sim \left\{ \begin{array}{l} \text{Normal}(\mu_B, \sigma), \text{t}= 1967, \ldots, 1991 \\ \text{Normal}(\mu_B + \mu_B(t - 1991)/10, \sigma), \text{t}= 1992, \ldots, 2001 \\ \text{Normal}(\mu_A = 2 * \mu_B, \sigma), \text{t}= 2002, \ldots \end{array} \right\}$$

The statistical procedures for determining whether or not a doubling has occurred, or in the case of a linear trend, when it is likely to occur, involve inferences about the means.

2.1 Inference for sudden increase

2.1.1 Hypothesis test

One approach is hypothesis testing, where the null hypothesis is that doubling has not been achieved and the alternative is that average natural production has at least doubled.

$$
\begin{aligned}
H_o : \mu_A &< 2\mu_B \equiv \mu_A - 2\mu_B < 0 \\
H_a : \mu_A &\geq 2\mu_B \equiv \mu_A - 2\mu_B \geq 0
\end{aligned}
$$

This formulation is awkward in that under H_o, the set of possible values of μ_A is infinite and the most conservative value to choose for testing the μ_A is $2\mu_{B-}$, where μ_{B-} is infinitesimally smaller than μ_B. The underlying t-statistic that would be appropriate is identical to that for a mathematically less awkward formulation, namely,

$$
\begin{aligned}
H_o : \mu_A &\leq 2\mu_B \\
H_a : \mu_A &> 2\mu_B.
\end{aligned}
$$

This formulation is troublesome, however, in that if $\mu_A = 2\mu_B$, i.e., an exact doubling has occurred, then one would not want to reject H_o.

2.1.2 Lower confidence bound for $\mu_A - \mu_B$

A less awkward solution is to construct a 1-α lower confidence bound (LCB) for $\mu_A - \mu_B$. If the LCB is greater than or equal to μ_B, then that is evidence for a doubling of the average. The point estimate of $\mu_A - \mu_B$ is $\overline{P}_A - \overline{P}_B$, the difference in average production levels in the before and after time periods; i.e.,

$$
\begin{aligned}
\overline{P}_B &= \frac{1}{25} \sum_{t=1967}^{1991} P_t \\
\overline{P}_A &= \frac{1}{n_A} \sum_{t=1992}^{1991+n_A} P_t
\end{aligned}
$$

The standard error of the difference,

$$
SE(\overline{P}_A - \overline{P}_B) = \sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}},
$$

where s_B^2 and s_A^2 are the sample variances of production for the before and after periods and n_B and n_A are the number of years of data for both periods. If one assumes that the variance is the same for both time periods, then a pooled variance estimate would be calculated,

$$
s_p^2 = \frac{(n_B - 1)s_B^2 + (n_A - 1)s_A^2}{n_B + n_A - 2}
$$

and the standard error is,

$$SE(\overline{P}_A - \overline{P}_B) \;=\; s_p\sqrt{\frac{1}{n_A} + \frac{1}{n_B}},$$

The LCB, in this latter case, is

$$LCB(\mu_A - \mu_B) \;=\; \overline{P}_A - \overline{P}_B - t_{1-\alpha,n_B+n_A-2}SE(\overline{P}_A - \overline{P}_B)$$

It is likely that variances would change with changes in the mean production level, however, and the degrees of freedom calculation is a little more complicated, and not worth going into here.

One can also use this formulation to examine the effect of sample size on the precision of the inference. Assuming $\mu_A = 2\mu_B$, then the expected value of $\overline{P}_A - \overline{P}_B$ is μ_B. Suppose one would like the LCB for $\mu_A - \mu_B$ to be within a specified level below μ_B, say $k\mu_B$ where $0 < k < 1$. For example, suppose μ_B=800 and k=0.9, i.e., one wants the LCB to be at or above 0.9*800=720. The probability of this occurring can be calculated for various sample sizes or number of years of data as follows. For simplicity standard normal quantiles, z_α, are used to approximate t-distribution quantiles (which would be a bit more accurate); relatedly the common variance of production values, σ^2, is assumed known.

$$\Pr(LCB \geq k\mu_B) \;\approx\; \Pr\left(\overline{P}_A - \overline{P}_B - z_\alpha\sigma\sqrt{\frac{1}{n_A} + \frac{1}{n_B}} \geq k\mu_B\right) \tag{1}$$

Using the fact that

$$\overline{P}_A - \overline{P}_B \;\sim\; \text{Normal}\left(\mu_B, \sigma\sqrt{\frac{1}{n_A} + \frac{1}{n_B}}\right),$$

one can rearrange the terms in Eq (1) to get the result,

$$\Pr\left(Z \geq z_\alpha - \frac{(1-k)\mu_B}{\sigma\sqrt{\frac{1}{n_A} + \frac{1}{n_B}}}\right)$$

where Z is standard normal. n_B can be viewed as fixed at 25 (years 1967 to 1991). A reasonable α-level for the LCB is 0.05, thus z_α=1.96. Suppose μ_B=800, σ=200, and k=0.9. The probability in Eq (1) for different values of n_A, namely number of years after 1991 that are monitored are shown in the table below.

n_A	$z_\alpha - \dfrac{(1-k)\mu_B}{\sigma\sqrt{\frac{1}{n_A}+\frac{1}{n_B}}}$	$\Pr(LCB \geq 720)$
5	0.83	0.20
10	0.58	0.28
15	0.42	0.34
20	0.31	0.38
25	0.23	0.41
30	0.17	0.43
35	0.12	0.45
40	0.08	0.47
45	0.04	0.48
50	0.01	0.50
∞	-0.36	0.64

Note that the probability that the LCB exceeds 720 is at most 64%, no matter how many years of monitoring are carried out. The reason for this bound is the fixed number of years in the baseline period, n_B, that creates fixed uncertainty about μ_B and therefore about $\mu_A - \mu_B$.

2.1.3 Bayesian solution

A Bayesian perspective is to view μ_A and μ_B as random variables in the sense that our knowledge about them is uncertain (as opposed to μ_A and μ_B truly varying, say from year to year). One way of framing our inference objective now is to calculate a probability statement of the following form.

$$\Pr(\mu_A \geq 2\mu_B | Data),$$

equivalently

$$\Pr(\mu_A - 2\mu_B \geq 0 | Data). \tag{2}$$

Such inferences about parameters made conditional on the data are called inferences from the posterior distribution for the parameters. The determination of a posterior distribution requires specification of a prior distribution for the parameters and a likelihood or probability model that links the data to the parameters. Bayes theorem then can be used to calculate the posterior distribution. In general if θ is a parameter, the posterior distribution for θ is

$$
\begin{aligned}
\Pr(\theta | Data) &= \frac{\Pr(\theta, Data)}{\Pr(Data)} = \frac{\Pr(Data | \theta) \Pr(\theta)}{\Pr(Data)} \\
&= \frac{\Pr(Data | \theta) \Pr(\theta)}{\int \Pr(\theta, Data) d\theta} \\
&= \frac{\Pr(Data | \theta) \Pr(\theta)}{\int \Pr(Data | \theta) \Pr(\theta) d\theta}
\end{aligned}
$$

where $\Pr(\theta)$ is the prior distribution. Note that the denominator $\Pr(Data)$ can be evaluated by averaging the probability of the data and θ, combined, over all possible values of θ. In short, Bayesian inference uses data to update or modify a prior distribution, thus yielding a posterior distribution.

In many cases to calculate the posterior distribution requires numerical computation methods, often computer intensive Monte Carlo procedures. To demonstrate how the method would work here, however, a simplifying choice of prior distributions is made, namely, that the priors for μ_A and μ_B are independent normal random variables with the same mean μ and same variance γ^2. This implies that before viewing data we do not believe there has been any change in production levels from the baseline period. γ^2 should be chosen to be relatively wide to reflect our uncertainty about the two means. We further assume (as for the LCB calculations above) that the production values ($Data$) are independent normal random variables given the parameters, μ_A and μ_B, and the variance is the same (σ^2). After some algebra, one can show that the resulting posterior distributions for μ_A and μ_B are independent normal distributions:

$$\mu_B|Data \sim \text{Normal}\left(\frac{\sigma^2}{\sigma^2 + n_B\gamma^2}\mu + \frac{n_B\gamma^2}{\sigma^2 + n_B\gamma^2}\overline{P}_B, \frac{\sigma^2}{\sigma^2/\gamma^2 + n_B}\right) \tag{3}$$

$$\mu_A|Data \sim \text{Normal}\left(\frac{\sigma^2}{\sigma^2 + n_A\gamma^2}\mu + \frac{n_A\gamma^2}{\sigma^2 + n_A\gamma^2}\overline{P}_A, \frac{\sigma^2}{\sigma^2/\gamma^2 + n_A}\right) \tag{4}$$

The Bayes solution to the probability in Eq (2) can be found by evaluating the following integral.

$$\Pr(\mu_A - 2\mu_B \geq 0|Data) = \int_{-\infty}^{\infty}\left[\int_{2\mu_B}^{\infty} f(\mu_A|Data)d\mu_A\right] f(\mu_B|Data)d\mu_B, \tag{5}$$

where $f(\mu_A|Data)$ and $f(\mu_B|Data)$ are the posterior (normal) density functions (Equations (3) and (4)).

As a demonstration the before (n_B=25) and after (n_A=30) production values were simulated.

$$P_t \sim \left\{ \begin{array}{ll} \text{Normal}(\mu_B = 765, \sigma = 200) & \text{t= 1967,\ldots,1991} \\ \text{Normal}(\mu_A = 2*\mu_B, \sigma = 200) & \text{t= 1992,\ldots} \end{array} \right\}$$

The priors for μ_B and μ_A were independent Normal(μ=600,τ=400). The resulting production means were $\overline{P}_B$=748 and $\overline{P}_A$=1473. The posterior distributions,

$$\mu_B|P_{1967},\ldots,P_{1991} \sim \text{Normal}(746, 36)$$
$$\mu_A|P_{1992},\ldots,P_{2021} \sim \text{Normal}(1465, 36).$$

The probability that μ_A is at least double μ_B was estimated by Monte Carlo integration:

$$\Pr(\mu_A \geq 2\mu_B) \approx 0.37.$$

Note that μ is exactly $2\mu_B$ in this case, but there is enough uncertainty about μ_B in particular that even increasing n_A to 3000 years only increases this probability to around 72% (the argument is similar to issue of limits on a LCB's precision). If in fact μ_A were $2.2\mu_B$, then $\Pr(\mu_A \geq 2\mu_B)$ (given n_B=30 years) increases to 94%. It is simply more difficult to establish that natural production has doubled if it has increased increased by a factor of 2.0 as compared to a factor of, say, 3.0 (i.e., "much more than doubled").

2.2   Inference for linear increase

We just consider one parametric formulation to the issue of trend in this idealized setting. The focus is on *estimating* trend and *predicting* when a doubling might be achieved; this is in contrast to *testing* for trend. The underlying model for production is assumed to be:

$$P_t \sim \begin{cases} \text{Normal}(\mu_B, \sigma) & t = 1967, \dots, 1991 \\ \text{Normal}(\mu_B + \beta(t - 1991), \sigma) & t = 1992, \dots, T \\ \text{Normal}(\mu_A = 2 * \mu_B, \sigma) & t \geq T, \dots \end{cases}$$

The year T is unknown and the methodology below assumes that $1991 + n_A$ is some point in time before T. One could develop a more general methodology to deal with the case $n_A > T$ and determining this change point is an additional inference problem.

Given n_A years of production values, the slope, β, is estimated by ordinary least squares.

$$\hat{\beta} = \frac{\sum\limits_{t=1992}^{1992+n_A-1} (P_t - \overline{P})(t - \bar{t})}{\sum\limits_{t=1992}^{1992+n_A-1} (t - \bar{t})^2}$$

To predict when $\text{E}[P_t] \geq 2\mu_B$, solve for T in the equation,

$$2\mu_B \geq \mu_B + \beta(T - 1991)$$
$$\Rightarrow$$
$$T \leq \mu_B/\beta + 1991$$

Thus if $\mu_B = 700$ and $\beta = 100$, then $T \leq 7 + 1991 = 1998$ (in this case $T=1998$ is the year doubling is achieved). Given an estimate of μ_B (the intercept in the linear model), the predicted value for T:

$$\hat{T} = [\hat{\mu}_B/\hat{\beta} + 1991]$$

where the notation $[x]$ means to take the next largest integer for x if x is not an integer. For example, if $x=2.3$, $[x]=3$. Confidence intervals for $\hat{T}$ could be calculated, too.

Nonparametric curves could be fit as well. Additional refinements would be nonparametric functions restricted to be monotonically increasing functions (e.g., isotonic regression).

3   Complications

There are at least two complications to the true situation that are departures from the assumptions made under the idealized situation.

3.1   Measurement error

The first complication is that production for a given year and stock must be estimated, and estimated production differs from true production by measurement or observation error. This error has two components, bias and variance. For a given year, the estimate of production can be decomposed into three components,

$$\hat{P}_t \;\; = \;\; P_t + b_t + \epsilon_t, \tag{6}$$

where P_t is the true production, b_t is bias or systematic error in one direction, and ϵ_t is random error. ϵ_t is on average 0 and has some variance, denoted τ_t^2.

3.1.1   Bias

Ideally $b_t=0$, i.e., the estimates are unbiased and the average of multiple estimates of P_t would be quite close to P_t. If bias does exist and if the bias was constant from year to year, i.e., $b_t=b$ a constant, then some of the above procedures could still apply when inference centers on the difference, $\mu_A - \mu_B$. For example,

$$E[\overline{P}_A - \overline{P}_B] \;\; = [\mu_A + b] - [\mu_B + b] = \mu_A - \mu_B$$

3.1.2   Random error

Similar to bias, it would be simplest if τ_t^2 were constant for all years. It is likely not constant, however, but so long as estimates of τ_t^2 were available, relatively accurate inferential statements about $\mu_A - \mu_B$ are still possible.

3.1.3   Estimation of P_t

Estimation of P_t for a wild Chinook salmon stock is complicated and involves estimation of various components of catch (ocean and freshwater) and escapement. For the purposes of Title 34 there are two sets of production estimates to consider, the baseline period estimates and estimates made afterwards (from 1992 until some unspecified time in the future). Both sets of estimates will have bias and random error. We have serious concerns about baseline period estimates and make recommendations about procedures for making future estimates (see Section 6).

3.2   Dependence in P_ts

The second complication is that annual production levels, P_t, are not independent between years. One source of between year dependence arises from the fact that a single cohort contributes to the

production for multiple years. If, for example, the age 2 survival is very high for a cohort from brood year t, then that cohort will contribute larger than average numbers of fish to the age 2 component of P_{t+2}, to the age 3 component of P_{t+3}, and so on. Underlying this dependence is both demographic stochasticity (e.g., number of fry produced will vary between occasions with identical escapement and environmental conditions) and environmental stochasticity (e.g., river flows vary between years during juvenile residence).

To demonstrate the possible degree of between year dependency, simulations of abundances were made using a life history model for Sacramento winter-run Chinook salmon (Newman and Lindley *in prep*). Winter-run Chinook salmon return mostly at ages 2, 3, or 4. The simulation model generates outmigrating juveniles from a stochastic Beverton-Holt recruitment function. It also generates sex-specific age 2 ocean residing fish (non-maturing) and age 2 spawners using multinomial distributions (with parameters being survival rates and maturation rates). Multinomials are also used to generate age 3 and age 4 fish (sex-specific, immature and mature, where all age 4 fish are mature). The stochastic Beverton-Holt model and the multinomials generate demographic variation, and environmental variation is simulated by allowing the age 2 survival rate (survival from outmigrating juvenile phase to age 2 ocean phase) to vary at random. There is no harvest in the simulation.

Figure 2 shows a time series plot of the simulated production for a 60 year period along with an autocorrelation plot with lags up to 19 years. The autocorrelations are quite high for lags of one and two years, and are statistically significant (>0) for up to 4 years. In the presence of harvest, if the harvest varies much between years, the degree of between year dependence will likely lessen. In any case, testing or estimation procedures that ignore between year dependence will be potentially misleading.

3.3   Modifications to procedures for idealized situation

In the remainder of this section, we examine two modifications to some of the analysis procedures described in Section 2 and we focus just on the problem of measurement error. Modifications to procedures in Section 2 to reflect dependency alone can be made, for example, using an AR-4 model, (autoregressive model of order 4), but we defer treatment of dependency to Section 4. State-space models are a unified approach for handling measurement errors and interannual dependence simultaneously and details are given in Section 4.

3.3.1   Sudden change and measurement errors

The following model is assumed for production estimates.

$$\hat{P}_t | P_t \quad \sim \quad \text{Normal}(P_t, \tau_t), \ t = 1, \ldots, n_B, n_B + 1, \ldots, n_B + n_A$$

Thus conditional on the true production, the estimate is unbiased and has a variance that can vary from year to year. It can be shown that the probability distribution for $\hat{P}_t$ *unconditional* on P_t is

also normal and is the following.

$$\hat{P}_t \sim \text{Normal}\left(\mu_{Bt}, \sqrt{\sigma^2 + \tau_t^2}\right), \ t = 1, \ldots, n_B$$

$$\hat{P}_t \sim \text{Normal}\left(\mu_{At}, \sqrt{\sigma^2 + \tau_t^2}\right), \ t = n_B + 1, \ldots, n_B + n_A$$

Assuming that the variances in the estimates, τ_t^2, are known (or, more realistically variance estimates are available and then treated as equal to τ_t^2), the three parameters, μ_B, μ_A, and τ^2, can be estimated by maximum likelihood. The estimates are found iteratively (i.e, there is no closed form analytic solution) using a technique called Fisher scoring. The estimates at the $k+1$ iteration are found by the following formula.

$$
\begin{bmatrix} \mu_B^{k+1} \\ \mu_A^{k+1} \\ \sigma^{2(k+1)} \end{bmatrix} = \begin{bmatrix} \mu_B^k \\ \mu_A^k \\ \sigma^{2(k)} \end{bmatrix} + \begin{bmatrix} \left[\sum_{t=1}^{n_B} \frac{1}{\tau_t^2+\sigma^{2(k)}}\right]^{-1} & 0 & 0 \\ 0 & \left[\sum_{t=n_B+1}^{n_B+n_A} \frac{1}{\tau_t^2+\sigma^{2(k)}}\right]^{-1} & 0 \\ 0 & 0 & \left[\sum_{t=1}^{n_B+n_A} \frac{1}{\tau_t^2+\sigma^{2(k)}}\right]^{-1} \end{bmatrix} \begin{bmatrix} \sum_{t=1}^{n_B} \frac{\hat{P}_t-\mu_B^k}{\tau_t^2+\sigma^{2(k)}} \\ \sum_{t=n_B+1}^{n_B+n_A} \frac{\hat{P}_t-\mu_A^k}{\tau_t^2+\sigma^{2(k)}} \\ -0.5\sum_{t=1}^{n_B+n_A}\frac{1}{\tau_t^2+\sigma^{2(k)}} \\ +0.5\sum_{t=1}^{n_B}\frac{(\hat{P}_t-\mu_B^k)^2}{\tau_t^2+\sigma^{2(k)}} \\ +0.5\sum_{t=n_B+1}^{n_B+n_A}\frac{(\hat{P}_t-\mu_A^k)^2}{\tau_t^2+\sigma^{2(k)}} \end{bmatrix}
$$

A LCB for μ_A-μ_B can again be constructed and is equal to:

$$\hat{\mu}_A - \hat{\mu}_B - z_\alpha \sqrt{\left[\sum_{t=1}^{n_B} \frac{1}{\tau_t^2 + \sigma^{2(k)}}\right]^{-1} + \left[\sum_{t=n_B+1}^{n_B+n_A} \frac{1}{\tau_t^2 + \sigma^{2(k)}}\right]^{-1}}$$

The estimated variances of $\hat{\mu}_A$ and $\hat{\mu}_B$ are taken from the first two elements on the diagonal of the 3 by 3 matrix in the above iterative estimation procedure (the matrix is called the Fisher Information matrix).

3.3.2 Linear increase and measurement errors

Estimation of the slope parameter proceeds in similar fashion to the estimation in the sudden increase case. The unconditional distributions for $\hat{P}_t$ have variances increased by measurement errors.

$$\hat{P}_t \sim \begin{cases} \text{Normal}\left(\mu_B, \sqrt{\sigma^2 + \tau_t^2}\right), t = 1967, \ldots, 1991 \\ \text{Normal}\left(\mu_B + \beta(t - 1991), \sqrt{\sigma^2 + \tau_t^2}\right), t = 1992, \ldots, T \\ \text{Normal}\left(\mu_A = 2 * \mu_B, \sqrt{\sigma^2 + \tau_t^2}\right), t \geq T, \ldots \end{cases}$$

Maximum likelihood estimates for μ_B, β, and σ^2 can again be found using an iterative procedure such as Fisher scoring.

Given estimates of μ_B and β, T can be predicted as before,

$$\hat{T} \;\; = \;\; [\hat{\mu}_B/\hat{\beta} + 1991],$$

but now the variance estimate for $\hat{T}$ needs to be inflated somewhat to reflect measurement error.

4 State-space models for production and estimates of production

A single coherent framework that can account for error in production estimates and reflect interannual dependence in underlying true production levels is a state-space model (SSM). A SSM also has the ability to efficiently incorporate data generated from multiple sources for multiple components of production, e.g., juvenile abundances, catch, and escapement data. Additionally, depending upon the formulation of an SSM and available data, the resulting model can describe, and possibly explain, why production levels are what they are.

A SSM is a model for 2 time series, one called the state process (labeled $\mathbf{n}_t$) and the other called the observation process (labeled $\mathbf{y}_t$). A general formulation is the following.

$$
\begin{aligned}
\text{Initial state } \mathbf{n}_0 \;\; &\sim \;\; G(\theta) \\
\text{State process } \mathbf{n}_t \;\; &\sim \;\; G(\mathbf{n}_{t-1},\theta), t = 1, \ldots, T \\
\text{Observation process } \mathbf{y}_t \;\; &\sim \;\; F(\mathbf{n}_t,\theta), t = 1, \ldots, T
\end{aligned}
$$

where G and F denote particular probability distributions, e.g., normal or binomial and θ represents unknown parameters, e.g., measurement error and process error variances. Note that the model for the state process suggests that $\mathbf{n}_t$ only depends upon the immediate past $\mathbf{n}_{t-1}$; this is called a first order Markov process. The dependence can extend further in the past, but the model is technically no longer called a state-space model. We could use the term hidden process model for the more general case but will for simplicity stick with SSM even when dependence extends further in the past. Buckland, et al. (2004) give several example formulations of SSMs for animal population dynamics.

The inference objectives for SSMs are usually twofold: (1) to estimate the unknown parameters; (2) to estimate the unknown state values. To make such inferences, Monte Carlo procedures, including Markov chain Monte Carlo (Gilks, Richardson, and Spiegelhalter, 1996) and sequential importance sampling (Doucet, de Freitas, and Gordan, 2001), are typically used.

For the particular problem of detecting changes in average production, we consider two different SSM formulations. The first model is simpler and less explanatory than the second.

4.1 Simple SSM

This model focuses on total production rather than the components of production, catch and escapement. The between year dependence in production levels is treated somewhat as a blackbox

and observations are estimates of total production (along with estimates of variance). For example, in the case of sudden increase,

$$
\begin{aligned}
\text{Initial state } P_0 &\sim \text{Normal}(\mu_B, \sigma) \\
\text{State process } P_t &\sim \text{Normal}(\rho P_{t-1}, \sigma), t = 1, \ldots, n_B \\
P_t &\sim \text{Normal}(\mu_A, \sigma), t = n_B + 1 \\
P_t &\sim \text{Normal}(\rho P_{t-1}, \sigma), t = n_B + 2, \ldots, n_B + n_A \\
\text{Observation process } \mathbf{y}_t &\sim \text{Normal}(P_t, \tau_t), t = 1, \ldots, n_B + n_A
\end{aligned}
$$

The parameter ρ reflects the between year dependence in production levels, and the parameters σ and τ are the state process variation and observation error, respectively. The observation process could be lognormal instead of normal to ensure estimates are non-negative.

The state process is an example of a first order autoregressive model, where production in year t just depends upon the previous year's production. The model could be extended to second order as follows.

$$
\begin{aligned}
\text{Initial states } P_t &\sim \text{Normal}(\mu_B, \sigma), t = -1, 0 \\
\text{State process } P_t &\sim \text{Normal}(\rho_1 P_{t-1} + \rho_2 P_{t-2}, \sigma), t = 1, \ldots, n_B \\
P_t &\sim \text{Normal}(\mu_A, \sigma), t = n_B + 1 \\
P_t &\sim \text{Normal}(\rho_1 P_{t-1}, \sigma), t = n_B + 2 \\
P_t &\sim \text{Normal}(\rho_1 P_{t-1} + \rho_2 P_{t-2}, \sigma), t = n_B + 3, \ldots, n_B + n_A
\end{aligned}
$$

In the case of linear trend, with first order autocorrelation say, the state process model would include time and the previous production level.

$$
\begin{aligned}
\text{Initial state } P_0 &\sim \text{Normal}(\mu_B, \sigma) \\
\text{State process } P_t &\sim \text{Normal}(\rho P_{t-1}, \sigma), t = 1, \ldots, n_B \\
P_t &\sim \text{Normal}(\mu_B + \beta(t - 1991) + \rho P_{t-1}, \sigma), t = n_B + 1, \ldots,
\end{aligned}
$$

4.2 Production component SSM

In this SSM formulation individual components of production are separately modeled in the state process and the observations consist of estimates for each component and associated variances. The state and observation at time t are thus vectors of components. To reduce the number of equations slightly in the formulation below we assume that all age 4 fish mature; extending the model to allow age 5 fish is not difficult. Further, a distinction between freshwater and marine harvest is not made; again, a more complex model can be formulated to allow this. Observations are estimates of the components of production (and possibly abundances for other life history stages, especially juveniles). Thus the method of production estimation of Newman, Hicks, and Hankin (2004), for example, could be providing the estimates. As will be mentioned in Section 6, a considerably more complex SSM would include production estimation as part of the model, i.e., raw sample data rather than production estimates would serve as inputs or part of the observation vector.

The state process distributions are trinomial (Trin) for the catches and escapements and a rounded lognormal distribution for juveniles based on an underlying Beverton-Holt recruitment function. Alternate recruitment functions are easily substituted.

$$
\begin{aligned}
J_t \quad &\sim \quad [\text{Lognormal}] \left(\log \left(\frac{S_{2+3+4,t-1}\alpha}{1 + \beta(S_{2+3+4,t-1})} \right), \log(CV_{BH}{}^2 + 1) \right) \\
(C_{2t}, E_{2t}) \quad &\sim \quad \text{Trin}\left(J_{t-1}, \phi_2 h_2, \phi_2(1-h_2)\rho_2 \right) \\
(C_{3t}, E_{3t}) \quad &\sim \quad \text{Trin}\left(J_{t-2} - C_{2,t-1} - E_{2,t-1}, \frac{\phi_2(1-h_2)(1-\rho_2)\phi_3 h_3}{1-\psi_2}, \frac{\phi_2(1-h_2)(1-\rho_2)\phi_3(1-h_3)\rho_3}{1-\psi_2} \right) \\
&\qquad \psi_2 = \phi_2 h_2 + \phi_2(1-h_2)\rho_2, \\
(C_{4t}, E_{4t}) \quad &\sim \quad \text{Trin}\left(J_{t-3} - C_{2,t-2} - E_{3,t-2} - C_{3,t-1} - E_{3,t-1}, \frac{\phi_2(1-h_2)(1-\rho_2)\phi_3(1-h_3)\phi_4 h_3}{1-\psi_3}, \frac{\phi_2(1-h_2)(1-\rho_2)\phi_3(1-h_3)\phi_4(1-h_3)}{1-\psi_3} \right) \\
&\qquad \psi_3 = \phi_2 h_2 + \phi_2(1-h_2)\rho_2 + \phi_2(1-h_2)(1-\rho_2)\phi_3 h_3 + \phi_2(1-h_2)(1-\rho_2)\phi_3(1-h_3)\rho_3
\end{aligned}
$$

The observation vector would consist of estimates of age 2, 3, and 4 catches and escapements, and potentially estimates of outmigrating juveniles. Normal or lognormal distributions could be used.

Changes in production would be reflected in the state process and there are several ways to do this. If juvenile estimates are available, then increases in production could be modeled by increases in the α parameter of the Beverton-Holt model (partially reflecting increases in in-river juvenile survival rates) and/or by decreases in the β parameter (reflecting reduced density dependent mortality or increased habitat availability). With the sudden increase scenario, the α parameter could increase at the change point to some arbitrary amount; similarly β could decrease. With the linear trend model, the α parameter would be modeled as a function of time, just as production itself was in earlier examples. If juvenile estimates are not available, then increases in α and age 2 survival rates ϕ_2 are confounded, thus increases in production could be due to better in-river juvenile survival rates or better marine conditions. Models which allow for dynamic juvenile production parameters are discussed in the next section.

5   Sustainability of production

A review of scientific and statistical literature revealed that the situation created by Title 34, namely one of an ecosystem being in one state prior to some point in time (prior to 1992) and then changing to another state at some later point, is one that has been extensively dealt with. The literature has been largely motivated by the need for environmental impact statements (both for planned development and for after-the-fact assessment of environmental disasters, such as the Exxon Valdez oilspill) and ecosystem restoration projects (as is the intent of Title 34).

There are two distinct aspects to an assessment of a potential change in an ecosystem. One aspect is simply to determine if a change did occur, in terms of the abundance of one or more species, for example, and to estimate the effect size. The second aspect is to determine whether the event or project of interest caused a change in the ecosystem. These two aspects are analogous to the twin objectives of Title 34: (1) double production and (2) have the doubling be caused by

the ecosystem restoration that is taking place in the Sacramento-San Joaquin watershed system. The second objective has been phrased as having the doubling of production be sustainable. The previous three sections have focused on determining whether the first objective is met, and now we look at the second objective.

Ignore momentarily the complications of measurement error and between-year dependence in production levels, and consider the idealized situation of a sudden increase in average production and the method of a lower confidence bound on the difference, $\mu_A - \mu_B$. Suppose that an LCB on the difference is more than twice μ_B, thus providing strong evidence that a doubling has occurred. There is absolutely no assurance, however, that the doubling is due to ecosystem restoration, an improvement in conditions affecting ocean survival could be the cause, as could be changes in the age-specific harvest rate configuration (see Appendix A).

An underlying question for sustainability is "What changes in the ecosystem will result in a fundamental, longterm change in the expected production?". As restoration efforts indicate such changes are thought to be changes in fisheries habitat; e.g., introducing spawning gravel at sites in the mainstem Sacramento River, dam removals on Butte Creek, screening a major irrigation diversion on the Yuba River, improved water operations on the Stanislaus River (Andrew Hamilton, personal communication). Such efforts aim to increase the amount of habitat and the quality of existing habitat. With reference to a life history model, such as one embedded in the production component state-space model formulations, such changes could be manifested by changes in the downstream migrants/spawner and density dependent parameters of a recruitment model, where recruitment is defined by number of fry, say, and by changes in the expected in-river survival rates between fry and outmigrating smolt stages.

Considering the entire life history of Chinook salmon, the key to sustainability are survival rates: (a) egg to fry to tributary outmigrant; (b) tributary outmigrant survival through the Sacramento River and delta system to the ocean; (c) ocean survival rates to age 2; (d) ocean survival rates between successive ages (which reflects harvest rates). Fecundity (# eggs per fish or per body weight or age) varies significantly between individuals within a given year, but does not show much variation across years (except perhaps for strong El Nino-type events) and is therefore not a substantial determinant or measure of changes in the success of a population in a given environment. Improvements in instream freshwater habitat conditions should increase both (a) and (b) above and together will affect the magnitude of the fecundity parameter of a recruitment function. Increased habitat availability (e.g., the removal of a barrier to upstream migration) instead will increase total production (e.g., decreasing the value of the density dependence parameters in recruitment functions).

We maintain that the ultimate measure of sustainable production is the expected juvenile production over a long time period with age-specific harvest rates and marine survival rates held constant, or controlled for. An index of this expected juvenile production, that controls for spawners, is the expected maximum recruitment multiplied by expected survival rate between fry and outmigrating smolt stages. For the purpose of demonstration alone, consider a Beverton-Holt recruitment function, namely,

$$Fry \;\; = \;\; Spawners \frac{\alpha}{1 + \beta \; Spawners}.$$

The index of expected maximum recruitment, labeled *MJPI*,

$$MJPI \;\; = \;\; \frac{\alpha}{\beta}\mu_{\phi_r},$$

where μ_{ϕ_r} is the expected survival rate (in-river) of fry to outmigrating smolt. Note that unless fry are measured as well as outmigrating smolts, there is no way to distinguish increases in α from μ_{ϕ_r}, however. Thus it is nearly equivalent (whether or not exactly equivalent depends upon the underlying probability distributions) to redefine the recruits to be outmigrating smolts and then

$$MJPI \;\; = \;\; \frac{\alpha^*}{\beta} \tag{7}$$

where α^* reflects both fry/spawner, say, and in-river survival.

As defined above then, to determine sustainability, estimates of $MJPI$ are needed. Models which incorporate life history processes as well as demographic and environmental stochasticity are thereby needed and a state-space model with life history embedded in the state process seems appropriate. That an SSM also explicitly accounts for measurement errors is a further advantage.

Returning to the scenarios of a sudden increase or a trend, such changes would manifest themselves by changes in the *MJPI*, in particular by increases in α^* and/or decreases in β. It would be best if one would *a priori* specify which parameter is expected to be changing as a result of the particular habitat restoration efforts, with different α^* and β values allowed for different stocks in different watersheds. Similar to the approaches taken previously under idealized situations, α^*, for example could be allowed to have one value in the baseline period and another afterwards, under the sudden increase scenario, or have α^* be an increasing function of time after the baseline period. For example, the sudden increase case:

$$\alpha_t^* = \left\{ \begin{array}{ll} \alpha_B^* & t = 1967, \ldots, 1991 \\ k\alpha_B^* & t = 1992, \ldots \end{array} \right\}$$

where $k \geq 1$.

A further complication remains, however, in that even evidence of an increase in $MJPI$ does not imply that habitat restoration efforts *caused* the increase. Restoration efforts on each watershed can be viewed as part of an observational study in contrast to a designed experiment. The "treatments" or the restoration efforts are not applied at random to particular watersheds or sections of watersheds. Thus there is the possibility that observed increases in $MJPI$ are due largely to other changes in ecosystem conditions, e.g., higher than average water flow levels. As always, in an observational study there is the danger of confounding factors, other variables not manipulable by the scientist or manager, that affect the response of interest (and possibly interact with the treatment).

Two statistical tools aimed at lessening the potential impact of confounding factors are the use of controls and the use of covariates. For controls, one would like to find stocks (implicitly, streams) that have not experienced restoration efforts and are thought to have yielded production levels somewhat proportional to those of the restored stocks during the baseline period. During the period after restoration efforts, production levels for the control stock should roughly parallel

what *would have happened* to the treatment stock in the absence of treatment. Figure 3 shows an example of such a situation for both the sudden increase and linear trend cases. Such a design is called a Before-After Control-Impact or BACI design (Stewart-Oaten, Murdoch, and Parker, 1986), or more accurately a BACI Paired design (Smith 2002) in that multiple measurements are taken over time at both the control and "impact" (restored) sites. A standard procedure for analyzing such designs is a two-sample t-test comparing the average differences between control and impact sites in the before and after periods. More than one control site can be included, as well, in the design and then the analysis is a type of ANOVA (Underwood 1994).

The standard analyses of BACI designs, however, assume no measurement error and no temporal dependence. Once again a state-space model seems an appropriate tool for analysis. In this case the state and observation vectors would be extended to include values and measurements taken on the control site (stock). The underlying state process might assume identical, or nearly so, environmental variation.

The other statistical tool for dealing with confounding factors is the use of covariates. An example is the use of analysis of covariance (ANCOVA) whereby comparisons are made between a treatment and a control group (or multiple treatment and control groups) with covariates thought to influence the response of interest included in the model, hence "controlled for". For example when comparing mortality rates of male smokers and non-smokers, the man's age is a confounding factor and is thus included as a covariate in the model for mortality rate and an "age-adjusted" effect of smoking is reported. A similar device could be used by including covariates in the modeling of the parameters of the state process. For example, if a restoration project is carried out in some year after 1991, its possible effect on the α^* parameter could be modeled by included a dummy variable for a change beginning that year.

Covariate information for the baseline and later periods could perhaps be provided by using existing hatchery release and recovery data for adipose-clipped and coded-wire-tagged fish from Central Valley hatcheries. In particular year-specific indices for river and ocean survival rates might be developed from such data. The contrast between survival rates or indices for fish released at different locations in the Sacramento system could provide some assessment of impacts in the Sacramento system as opposed to the ocean. Variation across years would then provide a measure of temporal variability in these same survival rates.

There are a lot of unworked details still to consider with regard to the formulation and fitting of a state-space model aimed at determining sustainability. For example, for a BACI analysis, control sites, which have production estimates during the baseline period, would need to selected. Potential biases in baseline period production estimates are another issue (discussed later). The use of a state-space model that includes control stocks and covariates, however, is in principle a sound approach.

6 Discussion

6.1 Selection of approaches for detecting doubling and determining sustainability

Statistical methods for comparing current production levels with the baseline period levels are complicated by two factors: errors in the estimates of production and temporal dependence in production levels. Standard elementary procedures for comparing means, such as t tests and t-based confidence intervals for differences in means, or elementary procedures for estimating trends, such as regression models, are based on assumptions of no measurement errors and independence between observations. State-space models explicitly incorporate measurement error and temporal dependence and appear to be the best framework for comparing baseline and current production levels.

State-space models are also a potential tool for achieving the second objective of determining whether changes in production are sustainable. There are additional data needs and additional complications to the formulation of the model. In particular, to better make the case that ecological restoration efforts are responsible for increases in production, information from "control" sites and/or the inclusion of relevant covariates to model life history parameters, namely recruitment parameters, are needed.

We want to make clear that while state-space models appear to be the best tool, we have three concerns that need to be considered before attempting to fit a state-space model. The concerns are:

1. The quality of estimates of baseline period production.

2. The need for estimates of the imprecision, and potential bias, in baseline production estimates.

3. The need to be gathering data now that will allow unbiased, or negligibly biased, estimates of production and also yield estimates of imprecision.

In the remainder of this report we discuss each of these concerns in more detail.

6.2 Concerns Regarding Existing Estimates of Natural Production

In previous sections, we have provided sketches of a number of possible statistical methods that could conceivably be used to determine if abundance trends for natural production of CV Chinook salmon might support a conclusion that a sustainable doubling of production has or has not taken place by some fixed date. Potential application of these statistical methods is complicated by two factors. First, the CVPIA itself and Appendix A of the Final Restoration Program for the Anadromous Fish Restoration Plan (USFWS, 2001) both seem to call for doubling to be achieved on river- or stream-specific bases. Section 3406 (b)(1) of Public Law 102-575 states, in part: "...

natural production of anadromous fish *in Central Valley rivers and streams* will be sustainable, on a long-term basis, at levels not less than twice the average levels attained during the period of 1967-1991...” And, at Appendix A-15 of the Final Restoration Program, it is stated that: “Numeric restoration goals for Chinook salmon *in each stream* will be calculated as at least double the average of $P_{X,N,XX}$ for each of the years during the baseline period.” Together, these statements leave little doubt that it would not be enough to double *overall* natural production of, say, fall-run Chinook salmon in Central Valley streams. Instead, production is to be doubled, on a sustainable basis, in individual tributary streams.

Associated with this legal requirement that doubling be achieved on a stream-specific basis is a corresponding requirement that data be available on a stream-specific basis. For reasons that will become apparent below, this requirement complicates generation and analysis of data that might conceivably be used to assess abundance trends with respect to the CVPIA doubling mandates.

6.2.1 Methods Used to Generate Existing Data (1967-present)

In this section we first present a brief summary of the methods that have been used to generate stream-specific estimates of natural production for Central Valley streams. Our attention is centered on fall-run Chinook salmon because we have greatest experience with this race or run type and also because it is by far the dominant race of Chinook salmon in the system today. The essential analysis methods that have been applied to fall-run Chinook salmon have also been applied for other races (spring-, late-fall- and winter-runs) of Central Valley Chinook salmon, however, and we briefly point out the special problems that these other races present as compared to fall-run Chinook salmon. Our summary relies on our examination of three essential types of documents: (1) A compilation of CV annual freshwater run size, harvest and population estimates (Mills and Fisher 1994); (2) Appendix A of the Final Restoration Program for the Anadromous Fish Restoration Plan (USFWS, 2001); and (3) LOTUS-123 computer spreadsheets KINGPROD.WK3 and CHINOOKPRODUPDATED.62503c.123 (R. Burmester, USFWS, pers. comm.). The Miller and Fisher (1994) publication apparently provides the authoritative freshwater escapement and hatchery return data from 1967 through 1991 and was prepared to allow implementation of the CVPIA. The AFRP Appendix (USFWS, 2001) provides technical guidance regarding how ocean catch and other issues are to be incorporated in estimates of stream-specific natural production; the two computer files reflect inter-agency attempts to apply the guidance provided in the AFRP Appendix. To the best of our knowledge, the values that are currently presented in CHINOOKPRODUP-DATED.62503c.123 are those that would be subjected to the statistical analysis methods that we have proposed in this report. Following our review of the methods that have been proposed and used to generate stream-specific estimates of natural production, we provide a critique of these methods, pointing out the most important assumptions that have been made and their probable importance with respect to overall errors of estimation. As appropriate, we briefly consider special complications that may arise when these same methods are applied to the three other runs of Chinook salmon.

Before presenting a summary and critique of methods that have been used to generate estimates

of natural production, we are obligated to present a rigorous definition of just what is being measured by *natural production*. Natural production consists of "fish produced to adulthood without direct human intervention in the spawning, rearing, or migration processes" (CVPIA Section 3403 (h)) and is defined, for a particular stream, as the sum of the (a) number of adult fish that are harvested in the ocean (commercial + recreational), (b) the number of adult fish that are harvested in freshwater, and (c) the number of adult fish that escape to spawn in that stream, or stray to a hatchery on that stream *in a particular year*. This definition of production differs from more formal definitions of production in that it excludes fish that were produced but were not caught or did not escape to spawn (i.e., natural mortalities). Also, for an age-structured species like Chinook salmon, this definition of production reflects the contribution of spawning adults from at least three different brood years as age 3, 4, and 5 adults that are caught or escape to spawn in year t were produced by adults spawning in years $t-3$, $t-4$, and $t-5$. As noted previously, this means that natural production values in successive years have substantial autocorrelation.

6.2.2 Summary of Methods

As indicated above, the obvious conceptual approach for calculation of the annual natural production of adults from a specific stream would be to simply add up the ocean catch plus freshwater catch plus freshwater spawning escapement from that stream. Unfortunately, data are not available that would allow that kind of direct stream-specific addition of the major components of production. Instead, a much more convoluted procedure must be used, as was proposed in Appendix A to the AFRP (USFWS, 2001). The notation used below simplifies and hopefully clarifies the notation presented in Appendix A, but is otherwise a faithful representation of the methods recommended in that Appendix:

Appendix A of AFRP

- Step 1. Calculate the total size of the freshwater run that enters stream i, R_i, as:

$$R_i = C_{F,i} + E_{S,i} + E_{H,i}$$

  where $C_{F,i}$ = freshwater catch from within stream i itself; $E_{S,i}$ = freshwater spawning escapement in stream i; and $E_{H,i}$ = hatchery spawning escapement in stream i.

- Step 2. Calculate ocean catch from stream i, $C_{O,i}$ as:

$$C_{O,i} = C_O \cdot \left[R_i / \sum_{i=1}^{k} R_i \right]$$

  where C_O = total estimated ocean commercial and recreational catch of adult salmon from the ports of San Francisco and Monterey, and $\sum_{i=1}^{k} R_i$ = total estimated freshwater run sizes of all k "populations" returning to the Central Valley. Note that the k populations include all recognized populations of fall-run Chinook salmon but also include all recognized populations of winter-, spring- and late-fall-run Chinook salmon.

- Step 3. Calculate lower river freshwater catch from stream i, i.e. freshwater catch that *excludes* catch in the tributary stream itself, $C_{L,i}$,as:

$$C_{L,i} = C_L \cdot \left[R_i / \sum_{i=1}^{k} R_i \right]$$

  where C_L = total lower river freshwater catch

- Step 4. Calculate the total production from stream i, $P_{T,i}$ as:

$$P_{T,i} = C_{L,i} + C_{O,i} + R_i$$

- Step 5. Calculate natural production from stream i, $P_{N,i}$ as a fraction of total production in stream i:

$$P_{N,i} = (1-h)P_{T,i}$$

  where h = proportion of total production from stream i that is attributable to hatchery production in that stream or elsewhere in the Sacramento/San Joaquin system.

Methods used in KINGPROD.WK3 and CHINOOKPRODUPDATED.62503c.123

Methods used to generate stream-specific estimates of natural production that are tabulated in the KINGPROD.WK3 and CHINOOKPRODUPDATED.62503c.123 computer files appear to be largely consistent with the methods proposed in the AFRP Appendix, but reflect absence of annual estimates of freshwater catches in tributary streams and/or in the lower Sacramento River and of the percentages of hatchery fish in various streams. Instead, inter-agency biologists apparently had to adopt more generic "guesstimates" of these values so as to generate the time series of stream-specific estimates of natural production that seem required under the CVPIA doubling goals mandate. These methods are summarized below using notation that is, so far as possible, fully consistent with that used to describe the AFRP methods:

- Step 1. Calculate stream-specific estimates of total freshwater production (catch + escapement) from stream i, R_i^*, using:

$$R_i^* = (1+u)(E_{S,i} + E_{H,i})$$

  where u is a fraction that accounts for *total* freshwater harvest (i.e., harvest in the lower Sacramento and harvest in a particular stream). Note that u is not a freshwater harvest rate. For example, if $u = .4$ and the sum of stream-specific spawning escapement and hatchery escapement were 1000,000 fish, then 40,000 additional fish would be accounted for by freshwater catches. The freshwater exploitation rate would there be $u^* = 40,000/(100,000 + 40,000) = 0.285$. Thus, the true exploitation rate, u^*, may in general be considerably less than the u values reported in KINGPROD and CHINPRODUPDATED.

- Step 2. Calculate total production of adults from stream i using:

$$P_{T,i} = R_i^* + C_O \cdot [R_i^* / \sum_{i=1}^{k} R_i^*]$$

This method seems largely consistent with the AFRP recommendations although it uses total freshwater run sizes (ie., including lower river catches) rather than just freshwater run sizes to streams to adjust total ocean catches to stream-specific ocean catches.

- Step 3. Calculate natural production of adults from stream i using:

$$P_{N,i} = (1 - h)P_{T,i}$$

6.2.3   Critique of Methods

The methods described above that have been used to generate existing estimates of natural production in streams entering the Sacramento-San Joaquin system have an obvious solid conceptual basis and would be unobjectionable if there were solid empirical data to support a number of very important assumptions or assumed values that are used in the calculations. Because it is difficult to determine the degree to which these assumptions are violated or assumed values are in error, it is exceptionally difficult to quantify the magnitude of errors that maybe contained in the existing estimates of natural production. Below we provide our initial assessment of the importance of assumptions and assumed values used in the above calculations.

Scaling Ocean Catches to the CV Ocean Catch Index

Chinook salmon originating from the Sacramento River have been subjected to intensive ocean commercial and recreational fisheries over the entire period 1967-91 and they continue to be subjected to intensive ocean fisheries today. According to the KINGPROD tabulation, over the period 1967-1998, average ocean harvest of Central Valley fall-run Chinook salmon was about 342,000 fish as compared to an average total freshwater return $(= \sum R_i^*)$ of 264,000 fish. Calculation of the ocean catch attributable to any particular CV stream is based on scaling the CV INDEX of ocean catch (estimated San Francisco + Monterey port commercial and recreational landings), C_O, by the fraction of freshwater returns that are attributable to a particular stream (either $R_i / \sum R_i$ or $R_i^* / \sum R_i^*$). There are two huge assumptions made in these calculations that are unlikely to be valid. First, the CV INDEX assumes that the total catch of Chinook salmon from the ports of San Francisco and Monterey should be equal to the total ocean catch of Central Valley Chinook salmon. As the geographic extent over which Central Valley Chinook salmon are caught extends at least through southern Oregon in most years and ocean distribution of Chinook salmon is known

to vary substantially across years, it is exceptionally difficult to imagine that this assumption is even remotely correct. Thus, even though ocean sampling programs probably generate essentially unbiased and relatively accurate estimates of total catch, there are no historic data on stock composition of ocean catches which might be used to evaluate the performance of the CV Index as an estimator of ocean catch of Central Valley Chinook salmon. Modern genetic stock identification methods, if applied in the context of ocean sampling designs, could probably deliver quantitative estimates of ocean catch composition in the future.

Even assuming for the sake of argument that the CV INDEX provides an accurate estimate of the total ocean catch of Central Valley Chinook salmon, the second assumption that is made in the scaling of ocean catches also invokes a highly problematic but apparently unstated assumption. The scaling factor used here is $R_i / \sum R_i$ or $R_i^* / \sum R_i^*$, essentially the fraction of all CV returns of Chinook salmon that are accounted for by stream i. To scale up in this identical fashion for *all* streams and races invokes an untenable assumption that all populations experience the same ocean exploitation rates or that somehow the combination of stock-specific maturation schedules, growth rates, and return times all magically result in the same fraction of fish being caught in the ocean as compared to returning to freshwater in a given year. It is well known, for example, that winter-run Chinook salmon are smaller at age and less susceptible to ocean capture than other stocks of Chinook salmon. Similarly, spring-run Chinook salmon generally mature, on average, at an earlier age and leave ocean fisheries for freshwater spawning streams several months in advance of fall-run Chinook salmon stocks, thereby reducing their duration of vulnerability to ocean fisheries. Finally, even within fall-run Chinook salmon stocks, differences in maturation schedules or mean lengths at age can have profound impacts on the relation between freshwater returns and ocean catches. At age 3, many fall-run Chinook salmon stocks are only partially vulnerable to ocean fisheries because only a small fraction of age three fish may exceed legal size limits. For many CV fall-run Chinook salmon stocks, mean ocean sizes at age 3 are often very large, however, and almost all age three fish may be vulnerable to ocean fisheries. The point here is that ocean fishery vulnerability likely varies substantially across stocks of CV Chinook salmon. Without detailed and stock-specific information on differences in maturation schedules and sizes at age among these stocks, it is impossible to judge how large "scaling" errors might be that result from use of the factors $R_i / \sum R_i$ or $R_i^* / \sum R_i^*$. We suspect, however, that they may be large.

Unknown Freshwater Harvest Rates and Contributions of Hatchery Fish

The actual calculations that appear to have been made in the KINGPROD and CHINPRODUP-DATED files rely on two critical parameters that lack a substantial empirical basis. These parameters are u, a parameter that is somewhat related to the overall freshwater exploitation rate, and h, the fraction of total production for a given stock type in a given stream (e.g., fall-run Chinook salmon in the American River) that can be attributed to hatchery production. There are no available time series for freshwater exploitation rates in the lower river or in specific streams because freshwater creel surveys have not been carried out on a long-term ongoing basis. The contribution of hatchery fish to production of Chinook salmon in CV streams is poorly understood for two primary reasons. First, marking programs have generally been deficient. For example, with the

exception of a very few years of experimental marking, essentially none of the approximately 8 million fall-run Chinook salmon released annually from Nimbus Hatchery on the American River have been marked. Second, large numbers of Chinook salmon from essentially all of the existing CV hatcheries have been released at locations far distant from the hatchery rearing locations. Such "off-site" release practices have in many cases improved survival rates and ocean contributions of hatchery fish, but they have also generated widespread straying (failure to return to hatchery or stream of origin) throughout the system. Such offsite release practices are no doubt responsible for the current lack of genetic differentiation among fall-run Chinook salmon stocks from at least the Mokelumne, American, and Feather rivers.

The table below presents a few of the values that have been used in the KINGPROD and CHINPRODUPDATED files to generate freshwater catches and to distinguish hatchery from natural production of fall-run Chinook salmon. These values have, with exceptions noted in the table, generally been applied over the full 1967-91 period and also in subsequent years.

Stream	u	h	comment
American R.	0.45	0.40	
Feather R.	0.20	0.40	0.00 for 67-69, 92-94
Mokelumne R.	0.10	0.40	
Battle Ck.	0.10	0.90	
Merced R.	0.05	0.10	0.00 for 67-72, 92-97
Stanislaus R.	0.05	0.00	
Tuolumne R.	0.05	0.00	
Yuba R.	0.10	0.00	
Butte Ck.	0.10	0.20	
Mill Ck.	0.10	0.20	
Clear Ck.	0.10	0.20	

Scrutiny of the above table will reveal that freshwater harvest of fall-run Chinook salmon is perceived to be relative modest (less than 10% of total freshwater returns) with the exception of the American and Feather rivers where there appear to be moderately intense freshwater fisheries. In most systems, therefore, absence of freshwater harvest data seems unlikely to have generated huge errors in estimates of total natural production. The wide range and somewhat conflicting values of h, however, are a cause of substantial concern as these multipliers have substantial impact on the estimates of natural production. In the absence of empirical data suggesting the degree to which values of h might vary across years, it is difficult to calculate the magnitudes of errors or bias that may result from application of generic constant values over an entire data set. One can, however, explore the implications of assuming a constant h value in a particular stream given estimates of spawning escapement and hatchery escapement in a particular river system.

To illustrate the potentially unlikely scenarios that are suggested as a consequence of an assumption of constant h, we used the American River fall-run Chinook salmon stock as an example. Although the h would normally be applied to the entire production from the American River, we instead apply this value only to the sum of American River spawning escapement and Nimbus

Hatchery returns in a given year. The product of $h(E_{S,i} + E_{H,i}) = H$, say, where $i =$ American River, should give the number of hatchery fish in the American River in a particular year. If, for the sake of argument, one assumes that all hatchery fish in the American River originate from Nimbus Hatchery, then the ratio $E_{H,i}/H$ should provide a "homing rate" for fish returning to Nimbus Hatchery in a given year. Over the period 1967-1998, the total recorded returns of fall-run Chinook salmon to Nimbus Hatchery ranged from a low of 3,600 adults to a high of 20,600 adults, but were relatively stable between about 5,000 and 13,000 fish, falling below 5,000 fish in only two years and exceeding 13,000 fish in only two years. Yet, over this same period the calculated values of homing rates, implied by the use of a constant value of 0.4 for h, ranged from 0.19 to 1.43 and exhibited wide variation. Variation in these calculated values of homing rate did not exhibit a pattern that seemed logically related to total hatchery returns or to total escapement, and the values exceeding 1.0 imply that more hatchery fish entered the hatchery than would have been accounted for in the entire river using the constant h values. Thus, it seems highly unlikely that use of a constant value of $(1 - h)$ would result in meaningful estimates of natural production from a given stream. Of course, the above hypothetical calculations must also be complicated by unknown straying of hatchery fish from other systems, a phenomenon that no doubt varies substantially across years as a function of release locations and relative survival rates for hatchery fish released from different facilities. Also, it is possible that some small fraction of wild fish enter Nimbus Hatchery.

6.2.4   Conclusions

Existing estimates of natural production of Chinook salmon in Central Valley streams must clearly have large errors, but it is extremely difficult to conjecture what the magnitudes of these errors might be or the degree to which estimates may be seriously biased. Although estimates of error should be available for mark-recapture estimates of spawning escapement, errors of estimated total natural production originate from many other sources in addition to errors of estimation of spawning escapement. It seems clear that numerous untenable assumptions had to be made and that several important parameter values had to be assumed known in order to allow generation of estimates of natural production for individual races and streams. Chief assumptions that are of concern to us are: (1) the use of the CV Ocean Index (San Francisco + Monterey estimated total ocean salmon catches) as an estimate of total ocean catch of Central Valley origin Chinook salmon; and (2) an assumption that catch:escapement ratios are the same for all CV stocks of Chinook salmon. Several critical parameter values have been assumed constant over the period 1967-1991 (and through to the present, so far as we can tell) and such assumed constancy seem untenable. The assumed parameter values that cause us greatest concern are those relating to the contribution of hatchery fish in various streams, particularly in the American and Feather rivers where $h = 0.4$ may cause hatchery contributions to be underestimated.

Because the magnitude of errors of existing estimates of natural production may be very large and because there is no compelling reason to believe that existing estimates are even approximately unbiased, it seems clear to us that any analysis methods that seek to assess whether or not doubling of natural production has taken place must somehow account for possibly large errors in the existing data that provide the baseline from which future natural production must be compared. We suspect

that careful data analyses might allow one to develop some decent notions of the kinds of errors that may exist in tabulated estimates of natural production, but we believe substantial effort would be required to generate such notions. In this preliminary work, we have not had time to explore such issues, but such work should be accomplished in the immediate future.

6.3 Data needs and future production estimates

6.3.1 Alternative production estimates for the future

We recommend that procedures for estimating Chinook salmon production developed by Newman, Hicks, and Hankin (2004) be implemented as an alternative to procedures used for the baseline period estimates. The procedure is similar to the "run reconstruction" approach described in Appendix A of the AFRP document (USFWS, 2001), but not identical. Estimates of stock-specific hatchery and natural (wild) production are based on designated tagged and marked *surrogate* hatchery stocks which represent particular natural stocks.

A computer program, *CFM Sim*, has been developed which simulates marking, tagging, and catch and escapement sampling levels and the resulting estimates of production. It is a tool meant to help fisheries managers determine appropriate data collection and generation levels, including levels of constant fractional marking (CFM). These procedures require certain kinds of data to be generated in addition to those currently being generated.

Work on the methodology for estimating wild production is incomplete in that a variance estimator has not been formally developed. Statistical bootstrapping or resampling is a likely approach to variance estimation. Additionally, the estimation procedure (based on what is called the method of moments) is not the most statistically efficient procedure and can, for example, yield negative estimates of production (a problem shared by the estimation procedures described in Appendix A of the AFRP document). Also, the approach does not use juvenile production data, which provide the most direction information about stream-specific productivity. A state-space model formulation for the production of wild salmon and associated hatchery surrogates is potentially the solution to all of these problems, but will require a considerable research effort to develop and implement. Note that the state-space model formulations presented in Section 4 take production estimates or components of production estimates (catch and escapement estimates) as input. A more unified SSM approach would take the "raw data", marked hatchery release and recovery numbers, catch and escapement sample data, as input and generate production estimates as part of the output.

6.3.2 The necessary data

No matter which particular procedure is used to estimate production, it seems clear that it is most important to be collecting certain kinds of data now, that the data be of sufficiently high quality for the purposes of estimating production, and to ensure that measures of the precision and accuracy

of the data are provided. Watershed specific escapement estimates of wild fish are one of the more crucial data, ideally with age- and sex-specific estimates. Estimates of ocean catch are important and believed to be of generally high quality. Estimates of freshwater catch, however, are lacking for several watersheds and cutbacks in the budget of California Department of Fish and Game have forced the closure of freshwater creel surveys.

The right kind of data includes age- and stock-specific estimates of catches and escapements: ocean, mainstem, and stream catches, hatchery and in-river escapements. This implies a need for taking scale samples of unmarked fish in the escapement, for example.

Additionally, estimates of the sex composition of catches and escapements, where possible, could be quite useful (particularly for dealing with sex-specific maturation rates and more meaningful spawner-recruitment models). We also argue for the selection of tagged and marked "indicator" hatchery stocks meant to represent or serve as surrogates for unmarked natural stocks. Relatedly, despite the difficulty of doing so, we would suggest attempting to tag and mark outmigrating juveniles from natural stocks in order to determine just how well indicator hatchery stocks represent natural stocks. Lastly, as has been partially implemented, estimates of juvenile production on a per stream basis are needed.

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A   The effect of age-specific harvest rates on production

Assuming that the underlying natural processes remain constant, changes in harvest rate practices alone can lead to dramatic changes in production.

Suppose the underlying juvenile production model is Ricker (α=4000, β=0.001) and assume lognormal variation (multiplicative variation in the juveniles produced at a given level of spawners) with σ^2=0.02. A program was written (in S-Plus) called `exp.product` that calculates expected production based on the Ricker model, lognormal variation, age-specific annual survival rates, age-specific maturation rates, and finally age-specific harvest rates for ocean and freshwater catches.

The example output shown below compares two different sets of age-specific harvest rates and the resulting expected catch, escapement, and production. The Ricker parameters are the same as are the survival rates (ϕ_2=0.02, ϕ_3=0.60, ϕ_4=0.70) and maturation probabilities (ρ_2=0.07, ρ_3=0.60). The harvest rates in the first example are 0.2 for age 2 fish in both marine and freshwater fisheries, 0.3 for age 3 fish in both fisheries, and 0.5 for age 4 in a single fishery (say freshwater alone). For the second example, age 2 and age 3 fish are harvested more intensively (0.4 and 0.6 for ages 2 and 3), but the age 5 harvest rate declines to 0.3.

```
exp.product(u2m=0.2,u2f=0.2,u3m=0.3,u3f=0.3,u4=0.5)

C= 3984 Esc= 3145 P= 7129


exp.product(u2m=0.4,u2=0.4,u3m=0.6,u3=0.6,u4=0.3)

C= 9780 Esc= 2486 P= 12265
```

By increasing the harvest on younger age classes, the catch levels increase, escapements decrease somewhat, and the production on the whole increases by 72% for the second example compared to the first.

Figure 1: Artificial examples of two idealized production doubling scenarios. The vertical line marks the division between the baseline and later periods. The dashed lines are the underlying mean values.

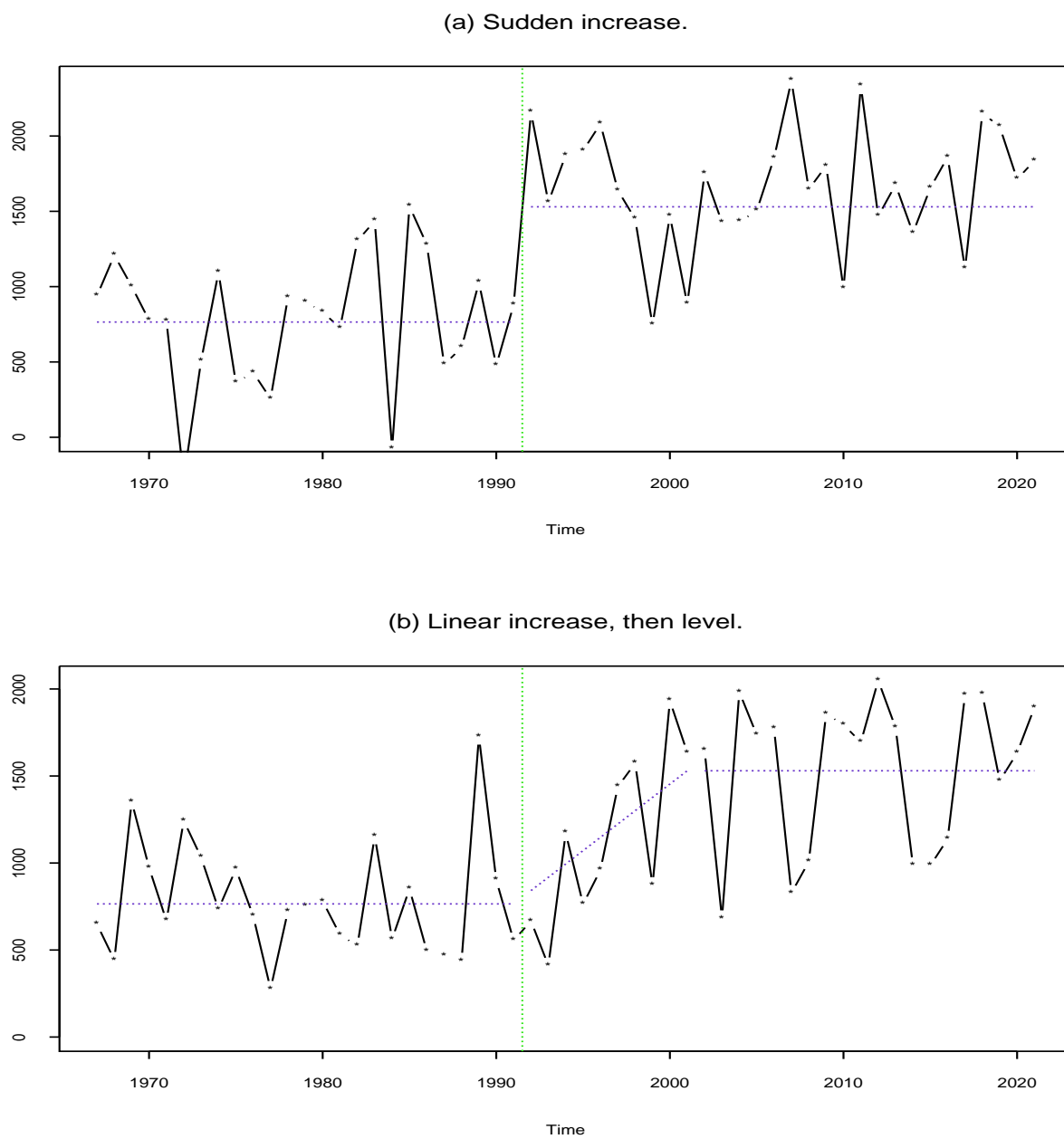(a) Sudden increase.

(b) Linear increase, then level.

Figure 2: Simulated production levels based on a model for winter-run Chinook salmon. All production is from escapement, harvest is zero. The horizontal dashed lines in the autocorrelation plot are the 95% confidence limits about 0 (no autocorrelation).
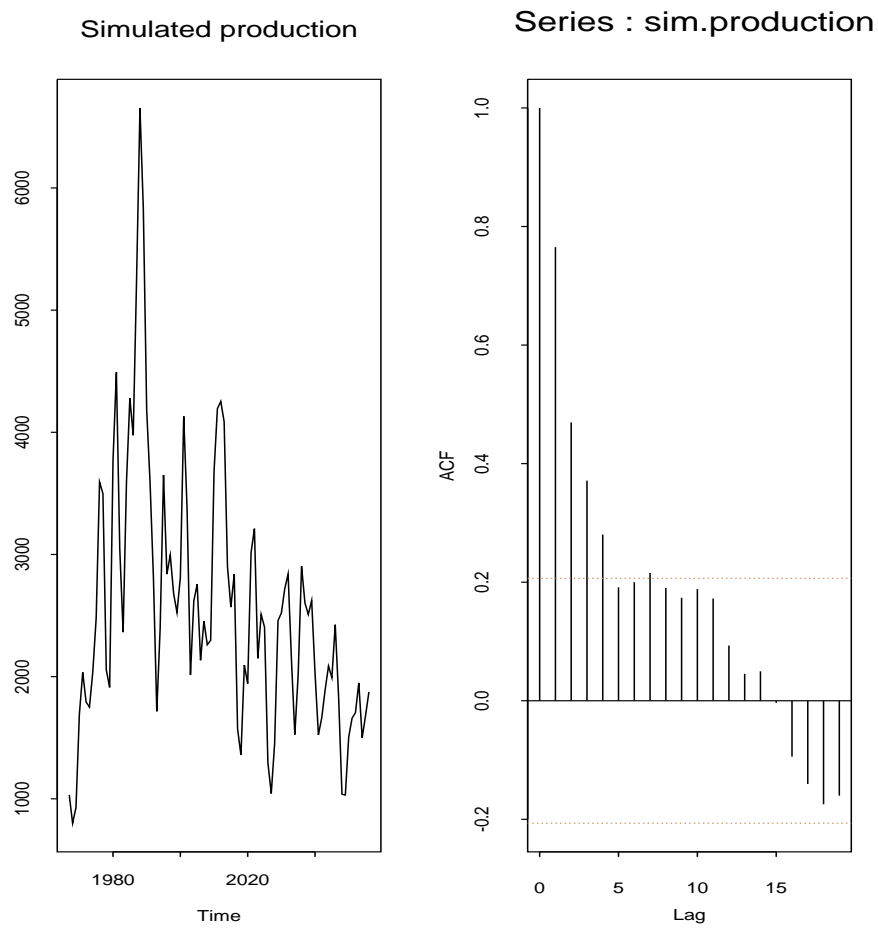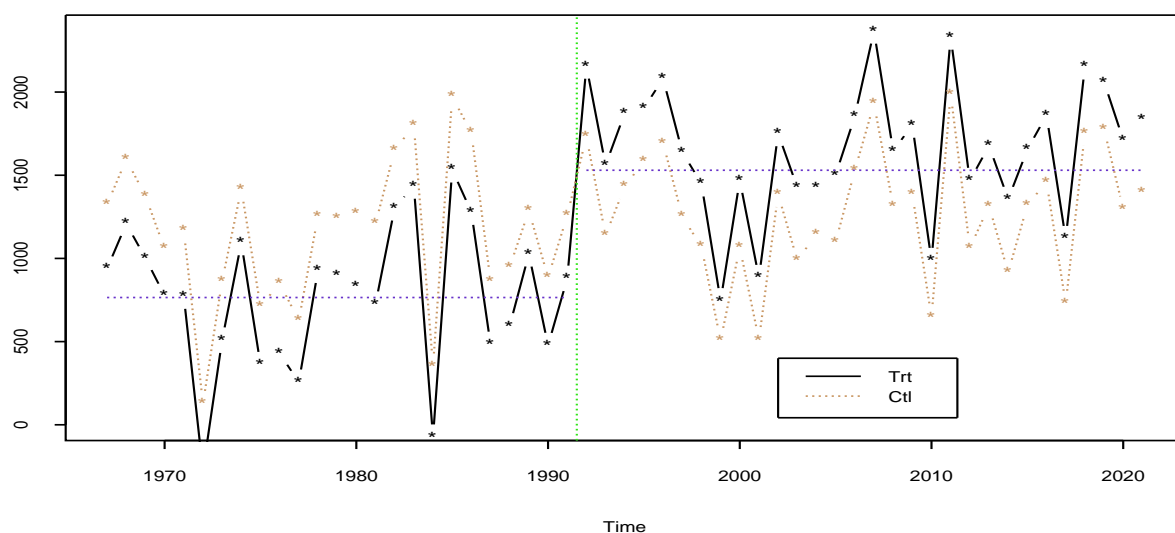
Figure 3: Artificial examples of two idealized production doubling scenarios along with the production of a control stock. The vertical line marks the division between the baseline and later periods. The dashed lines are the underlying mean values.

(a) Sudden increase (with control).

(b) Linear increase, then level (with control).